

Crop-damaging temperatures increase suicide rates in India

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SUPPORTING INFORMATION

1 Materials and methods

1.1 Data appendix

I compiled suicide and climate data at the state level for the years 1967-2013, and agricultural yield and climate data at the district level for the period 1956-2000. Summary statistics for key variables of interest are provided in Table S1.

Variable	Mean	(Std. Dev.)	Min.	Max.	N
<i>Suicide data: 1967 - 2013 (32 states)</i>					
Suicide rate (deaths per 100,000)	11.4	(11.9)	0	73.23	1472
Growing season daily degree days > 20°C	5.32	(2.93)	0	12.23	1645
Nongrowing season daily degree days > 20°C	3.85	(2.83)	0	9.56	1645
Growing season precip. (mm)	1186.18	(626.85)	111.16	4461.3	1598
Nongrowing season precip. (mm)	439.12	(361.48)	5.76	2148.4	1598
<i>Agricultural data: 1956 - 2000 (271 districts)</i>					
Log annual yield (Rupees per ha)	3.92	(0.72)	-1.87	6.45	11289
Growing season daily degree days > 20°C	6.7	(2.6)	0	14.99	11780
Nongrowing season daily degree days > 20°C	4.56	(1.79)	0	9.51	11780
Growing season precip. (mm)	870.55	(467.27)	10.74	4663.99	11780
Nongrowing season precip. (mm)	205.18	(185.12)	0.83	1577.09	11780

Table S1: Summary statistics

Note: Suicide data are from India's National Crime Records Bureau and are reported annually at the state level. Yield data are from [11] and are reported annually at the district level, valued in constant rupees. Growing season is June-September, nongrowing season contains all other months. Precipitation is measured cumulatively. See below for details on the degree days variables.

Note that for estimation throughout the article, I use cumulative degree days, as described in Section 1.1.3, which sums the daily degree day values across an entire season. When reporting standardized effects in the main text, I use the within-state standard deviations in cumulative degree days. The

growing season within-state standard deviation of cumulative degree days is 51 in my suicide sample and 44 in my yield sample.

1.1.1 Suicide data

I use annual suicide data as reported by the Indian National Crime Records Bureau (NCRB) at the state or union territory (UT) level from 1967 to 2013. States and UTs included in the data: Adaman & Nicobar Islands, Andhra Pradesh, Arunachal Pradesh, Assam, Bihar, Chandigarh, Chhattisgarh, Dadra & Nagar Haveli, Daman & Diu, Delhi, Goa, Gujarat, Haryana, Himachal Pradesh, Jammu & Kashmir, Jharkhand, Karnataka, Kerala, Lakshadweep, Madhya Pradesh, Maharashtra, Manipur, Meghalaya, Mizoram, Nagaland, Orissa, Puducherry, Punjab, Rajasthan, Sikkim, Tamil Nadu, Tripura, Uttar Pradesh, Uttaranchal, and West Bengal. I calculate suicide rates as the number of total suicides per 100,000 people, with population data linearly interpolated between Indian censuses.

Deaths in general are under-reported in India [4], and the suicide data provided by the NCRB are particularly problematic in this regard. The data are aggregated from district police reports; because attempted suicide was a criminal offense punishable under the Indian Penal Code until 2014, there is likely to be significant under-reporting of suicide as a cause of death. As evidence of this, the NCRB reports 135,000 suicides in India in 2010, while data from a nationally-representative cause of death survey calculates the value at 187,000 [20]. This under-reporting is likely uncorrelated with temperature and precipitation, implying my estimates of the response of suicide to climate provide lower bounds on the true marginal effect.

The evolution over time and space of state level suicide rates in India during my sample period is shown in Figure S1; darker shades indicate higher suicide rates. As a point of reference, suicide rates in the United States are currently approximately 12.5 per 100,000. There is clear spatial heterogeneity, with southern India experiencing the highest suicide rates and largest increases over time. These geographic differences can be seen in more detail for a subset of states in Figure S2. My empirical strategy accounts for this geographic heterogeneity by relying on within-state variation in order to avoid conflation of climate impacts with unobservables, such as cultural norms, political structures, and religious influences. Moreover, I account for spatially varying time trends, due to clearly distinct patterns over time across India (see Section 1.2 below for details).

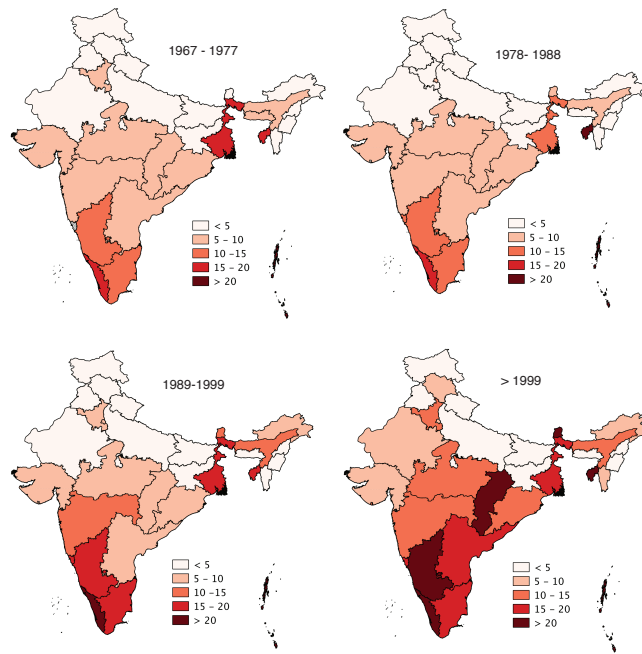


Figure S1: Evolution of suicide rates across space and time

Notes: This figure shows states colored by the average annual suicides per 100,000 people.

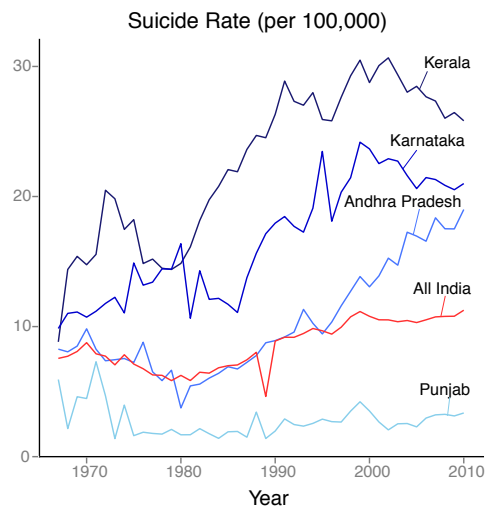


Figure S2: Evolution of suicide rates across time for four selected states, and on average across India

1.1.2 Agriculture data

I use agricultural data from [11]. These are district-level annual yield records for major crops (rice, wheat, sugar, sorghum, millet and maize) between 1956 and 2000, compiled from Indian Ministry of Agriculture reports and other official sources. These data cover 271 districts in 13 major agricultural states: Andhra Pradesh, Bihar, Gujarat, Haryana, Karnataka, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal. Districts are defined by the 1961 political boundaries. As noted in [4] and [11], these data importantly omit Kerala and Assam, two large agricultural producers that I find also have high rates of suicide. Rather than reporting quantities of each crop, these data provide log annual yield values of a production-weighted index across all crops measured in constant Indian rupees, where prices are fixed at their 1960-1965 averages (see [11] for details).

1.1.3 Climate data

Climate data are generally available at higher spatial and temporal resolution than social outcome data. Although suicides and yields are only measured annually, if the relationship between these outcomes and temperature is nonlinear, daily climate data are required, as annual average temperatures obscure such nonlinearities [16]. While existing studies on temperature and suicide in the epidemiology, sociology, or meteorology literatures do not explore nonlinearities, there are two reasons why they are likely to occur. First, the growing literature on climate and interpersonal conflict reviewed by [6] often identifies nonlinearities in the effect of temperature on violent crime. If we view suicide as a type of violence against oneself, it is possible that a similar relationship exists in this context. Second, [21], among others, have identified a strongly nonlinear response of staple crop yields to temperature. If suicide in India is indeed related to agricultural productivity, then capturing this nonlinearity is important.

For daily temperature data, I use the National Center for Environmental Prediction and National Center for Atmospheric Research (NCEP/NCAR) gridded daily reanalysis product, which provides observations in an irregular grid that is approximately $1^\circ \times 1^\circ$ [18]. These data include daily mean temperature for each grid over my entire sample period. To convert daily temperature into annual observations without losing intra-annual variability in daily weather, I use the agronomic concept of degree days. Degree days are calculated as follows, where T^* is a selected cutoff temperature value

and T is a realized daily temperature value:

$$D^{T^*}(T) = \begin{cases} 0 & \text{if } T \leq T^* \\ T - T^* & \text{if } T > T^* \end{cases} \quad (1)$$

Because there are multiple grid cells per state, I aggregate grid-level degree day values $D^{T^*}(T)$ to state-level observations using an area-weighted average (see Table S11 for robustness checks using weights based on population and area planted with crops). When these state-level degree day values are summed over days within a year, e.g. from day t to τ , regressing an annual outcome on cumulative degree days $\sum_{t=1}^{\tau} D^{T^*}(T_t)$ imposes a piecewise linear relationship in daily temperature, in which the outcome response has zero slope for all temperatures less than T^* . While a body of literature identifies biologically-determined cutoffs T^* for yields of variety of major crops, there is no empirical support to draw on in selecting T^* for suicides. Thus, while I use $T^* = 20^\circ\text{C}$ throughout the study, I also show robustness for a range of plausible cutoffs based on the distribution of my temperature data (see Tables S6 and S7), and in Figure 3 of the main text I estimate a flexible piecewise linear function using four different degree day cutoffs simultaneously to impose minimal structure on the response function (see Section 1.2 below for details).

Due to the fact that reanalysis models are less reliable for precipitation data [2], and because nonlinearities in precipitation that cannot be captured with a polynomial appear to be less consistently important both in the violent crime literature [6] and in the agriculture literature [21], I use the University of Delaware monthly cumulative precipitation data to complement daily temperature observations [22]. These data are gridded at a $0.5^\circ \times 0.5^\circ$ resolution, with observations of total monthly rainfall spatially interpolated between weather stations. Again, I aggregate grids up to states and districts using area-based weights, after calculating polynomial values at the grid-level.

1.2 Regression methods

To identify the impact of temperature and precipitation on annual suicide rates, I estimate a multivariate panel regression using ordinary least squares, in which the identifying assumption is the exogeneity of within-state annual variation in degree days and cumulative precipitation. Heterogeneity in suicide rates and in temporal trajectories across states, due to an interplay between unobservable cultural, political and economic factors, implies that cross-sectional variation in climate is endogenous. Thus, I use state and year fixed effects with state-specific time trends to control for time-invariant state-level

unobservables, national-level temporal shocks and regional trends.

Without precedent for the functional form of suicide’s relationship to climate, my primary estimation approach employs a flexible piecewise linear specification with respect to temperature and a cubic polynomial function of cumulative precipitation. To capture the distinct impact of economically meaningful climate variation, I separately identify the temperature and precipitation response functions by agricultural seasons. My empirical model takes the general form:

$$suicide_rate_{it} = \sum_{s=1}^2 \sum_{k=1}^{\kappa} \beta_{ks} \sum_{d \in s} DD_{idt}^k + \sum_{s=1}^2 g_s \left(\sum_{m \in s} P_{imt} \right) + \delta_i + \eta_t + \tau_i t + \varepsilon_{it} \quad (2)$$

Where $suicide_rate_{it}$ is the number of suicides per 100,000 people in state i in year t , $s \in \{1, 2\}$ indicates the season (growing and nongrowing), and $k = 1, \dots, \kappa$ indicates a set of degree day cutoffs that constrain the piecewise linear response. In my most flexible model I let $\kappa = 7$ with degree day intervals of 5°C, and in my simplest model I let $\kappa = 2$ and estimate a standard degree day model with just one kink point and two piecewise linear segments. DD_{idt}^k is the degree days in bin k (e.g. degree days between 10°C and 20°C) on day d in year t in state i , and P_{imt} is cumulative precipitation during month m in year t in state i . I estimate $g(\cdot)$ as a cubic polynomial. State fixed effects δ_i account for time-invariant unobservables at the state level, while year fixed effects η_t account for India-wide time-varying unobservables. In most specifications, I include state-specific time trends $\tau_i t$ to control for differential trends in suicide driven by time-varying unobservables. My identifying assumption is that, conditional on these fixed effects and trends, variations in daily temperature and monthly rainfall are as good as randomly assigned. Robustness to different fixed effects specifications is shown in the supplementary tables below.

Separately for each season, Equation 2 allows me to identify $\hat{\beta}_{ks}$, the estimated change in the annual suicide rate induced by one day in bin k becoming 1°C warmer. This annual response to a daily forcing variable is similar to that estimated and described in [9]. The polynomial response function for precipitation generates marginal effects of one additional millimeter of rainfall, again estimated seasonally. Due to likely correlation between errors within states, I cluster standard errors at the state level. This strategy assumes spatial correlation across states in any time period is zero, but flexibly accounts for within-state, across-time correlation.

1.2.1 Mechanism tests

With ideal data, I would estimate separate response functions for farmers and non-farmers to isolate the importance of an agricultural channel. Because my data do not provide the occupation of suicide victims prior to 2001 (and because using only post-2001 data at the state level leaves me statistically under-powered), I utilize a variety of other methods to investigate the validity of the oft-cited agricultural mechanism. The primary approach I take is to compare the significance and magnitude of each coefficient β_{ks} in Equation 2 across seasons. Temperatures and rainfall in June through September have been shown to be most critical for agricultural productivity [4], and thus should dominate the climate-suicide relationship if the agricultural channel is important. In a similar exercise, [12] and [3] demonstrate that monsoon-season precipitation impacts civil conflict and interpersonal crime in India, respectively, more than precipitation outside the growing season. Just as they use these findings as evidence of an agricultural channel through which climate affects crime and conflict, I use my results to identify the presence of an agricultural channel for suicide.

An additional method for examining mechanisms is to “pattern match” response functions [6]. For example, [15] show that the nonlinear relationship between agricultural income and rainfall in Brazil is nearly a perfect inverse of the relationship between land-invasion risk and rainfall. Similarly, [17] match the responses of conflict and income to the timing of the El Niño Southern Oscillation (ENSO), arguing that the results provide support for an income channel. I follow this approach by estimating Equation 2 using the log value of yield as the dependent variable in place of suicide rates. My estimating equation for the yield regression is:

$$\begin{aligned} \log_yield_{ct} = & \sum_{s=1}^2 \sum_{k=1}^{\kappa} \beta_{ks} \sum_{d \in s} DD_{c dt}^k + \sum_{s=1}^2 g_s \left(\sum_{m \in s} P_{c mt} \right) \\ & + \delta_c + \eta_t + \tau_i t + \varepsilon_{ct} \end{aligned} \quad (3)$$

Where the subscript c now indicates district, as my agriculture data are at the district-by-year level. δ_c are district fixed effects, η_t are year fixed effects, and $\tau_i t$ are state-specific linear trends. Standard errors are clustered at the district level. I use the response functions uncovered in Equations 2 and 3 to identify matching patterns between suicide and yield.

Finally, I look for further support of economic motives by exploring spatial heterogeneity of impacts.

For temperature shocks, I estimate a model that allows each of India's 32 states and union territories to have a distinct suicide rate response function:

$$\begin{aligned} suicide_rate_{it} = & \sum_{s=1}^2 \sum_{k=1}^{\kappa} \beta_{ks}^i \times \mathbb{1}[state = i] \sum_{d \in s} DD_{idt}^k + \sum_{s=1}^2 g_s \left(\sum_{m \in s} P_{imt} \right) \\ & + \delta_i + \eta_t + \tau_i t + \varepsilon_{it} \end{aligned} \quad (4)$$

I then look at correlations between these state-level temperature responses β_{ks}^i and analogous state-level temperature responses for log yield.

1.2.2 Adaptation

Figure 3 in the main text shows results from four sets of tests for adaptation. The exact specification for each regression model is shown below; all models use $\kappa = 2$ with a degree day cutoff of 20°C and include state-specific linear trends.

- **Fig. 3 A: Heterogeneity by long-run average climate**

I calculate the average degree days over the entire period for each state in the sample, and assign each state to a tercile of high, middle or low average degree days based on the national distribution. Let $avg_degday_tercile_i$ indicate the tercile of state i . I estimate:

$$\begin{aligned} suicide_rate_{it} = & \sum_{s=1}^2 \sum_{k=1}^{\kappa} \beta_{ks} \times \sum_{d \in s} DD_{idt}^k + \sum_{s=1}^2 \sum_{k=1}^{\kappa} \beta_{ks}^2 \times \mathbb{1}[avg_degday_tercile_i = 2] \sum_{d \in s} DD_{idt}^k \\ & + \sum_{s=1}^2 \sum_{k=1}^{\kappa} \beta_{ks}^3 \times \mathbb{1}[avg_degday_tercile_i = 3] \sum_{d \in s} DD_{idt}^k + \sum_{s=1}^2 g_s \left(\sum_{m \in s} P_{imt} \right) \\ & + \delta_i + \tau_i t + \varepsilon_{it} \end{aligned}$$

Note that in this regression, the first tercile is omitted, such that coefficients β_{ks}^2 and β_{ks}^3 are effects for the 2nd and 3rd terciles, relative to the 1st tercile.

- **Fig. 3 B: Heterogeneity by average income**

I use cross-sectional gross domestic product (GDP) per capita data for each state for the year

2010 from [13] to assign states to terciles of the national income distribution. I estimate:

$$\begin{aligned}
suicide_rate_{it} = & \sum_{s=1}^2 \sum_{k=1}^{\kappa} \beta_{ks} \times \sum_{d \in s} DD_{idt}^k + \sum_{s=1}^2 \sum_{k=1}^{\kappa} \beta_{ks}^2 \times \mathbb{1}[avg_income_tercile_i = 2] \sum_{d \in s} DD_{idt}^k \\
& + \sum_{s=1}^2 \sum_{k=1}^{\kappa} \beta_{ks}^3 \times \mathbb{1}[avg_income_tercile_i = 3] \sum_{d \in s} DD_{idt}^k + \sum_{s=1}^2 g_s \left(\sum_{m \in s} P_{imt} \right) \\
& + \delta_i + \tau_i t + \varepsilon_{it}
\end{aligned}$$

• **Fig. 3 C: Heterogeneity by temporal subsamples**

I estimate:

$$\begin{aligned}
suicide_rate_{it} = & \sum_{s=1}^2 \sum_{k=1}^{\kappa} \beta_{ks} \times \sum_{d \in s} DD_{idt}^k + \sum_{s=1}^2 \sum_{k=1}^{\kappa} \beta_{ks}^2 \times \mathbb{1}[period = 1983 - 1997] \sum_{d \in s} DD_{idt}^k \\
& + \sum_{s=1}^2 \sum_{k=1}^{\kappa} \beta_{ks}^3 \times \mathbb{1}[period = 1997 - 2013] \sum_{d \in s} DD_{idt}^k + \sum_{s=1}^2 g_s \left(\sum_{m \in s} P_{imt} \right) \\
& + \delta_i + \tau_s t + \varepsilon_{it}
\end{aligned}$$

Note that in this regression, the period 1967-1982 is omitted, such that coefficients β_{ks}^2 and β_{ks}^3 are effects relative to this earlier time period.

• **Fig. 3 D: Heterogeneity by frequency of climate variation**

The “panel” response is estimated as follows, with $\kappa = 2$ and a degree day cutoff of 20°C:

$$suicide_rate_{it} = \sum_{s=1}^2 \sum_{k=1}^{\kappa} \beta_{ks} \sum_{d \in s} DD_{idt}^k + \sum_{s=1}^2 g_s \left(\sum_{m \in s} P_{imt} \right) + \delta_i + \tau_i t + \varepsilon_{it}$$

The “long difference” estimate is discussed below.

1.2.3 Long differences estimation

My main estimation strategy exploits year-to-year variation in temperature and precipitation. To test whether there are adaptive behaviors that are infeasible in response to such short-run climate shocks, but become feasible at longer time scales, I estimate a “panel of long differences” empirical model in addition to the standard panel regression, the results of which are shown in Figure 3, panel D of the main text. This strategy follows closely the approach outlined in [5].

I first construct a moving average of the suicide rate and climate variables with a window of 5

years, over the entire sample. I then calculate the 10-year change in this average at four points in my sample: 1970, 1980, 1990 and 2000. That is, I collapse my data to 4 observations for each state in my data, where each observation measures the 10-year change in suicide rates and climate variables for each decade, and where these changes are “smoothed” by taking 5-year averages at the end points. I then estimate the effect of changes in average degree days and precipitation on changes in average suicide rates. This model takes the following form:

$$\Delta suicide_rate_{i\tau} = \sum_{s=1}^2 \beta_s \Delta DD_{is\tau}^k + \sum_{s=1}^2 \gamma_s \Delta P_{is\tau} + \delta_i + \nu_\tau + \varepsilon_{i\tau} \quad (5)$$

Where δ_i are state fixed effects, ν_τ are fixed effect for each of the four decadal starting points in my sample, s indicates the growing and nongrowing seasons, k indicates the degree day cutoff, and Δ indicates the 10-year change in each variable. I report results both including and excluding the state fixed effect δ_i and the decadal starting point fixed effect ν_τ . Results are shown in Section 2.6.

1.3 Impacts of recent climate trends

To compute estimates of the effect of warming temperature trends since 1980, I follow the approach outlined in [7] and [19]. I do not consider trends in precipitation, as my estimates for suicide impacts of precipitation were highly uncertain. Nor do I consider the impacts of warming outside the growing season.

For each state in my data, I estimate a linear trend in growing season degree days above 20°C for the years 1980-2013. Let the predicted value of degree days in state i in year t , as estimated by the trend, be indicated by DD_{it}^* . I then create a de-trended degree days residual that is normalized to temperature in 1980, for every state-year (see Figure S3):

$$DD_detrended_{it} = DD_{it} - DD_{it}^* + DD_{i,1980}^*$$

I predict suicide rates using actual and de-trended growing season degree days, using coefficient estimates from the model in Table 1 of the main text which includes both state trends and year fixed effects (column 3). The elevated risk of suicide attributable to the trend, relative to the de-trended counterfactual, is the difference between these two predictions, which simplifies to $\Delta s_{it} = \hat{\beta} \times (DD_{it} - DD_detrended_{it})$, where $\hat{\beta} = 0.008$ as estimated in my preferred empirical model. I multiply Δs_{it} — the increase in the suicide rate attributable to warming — by the population in each

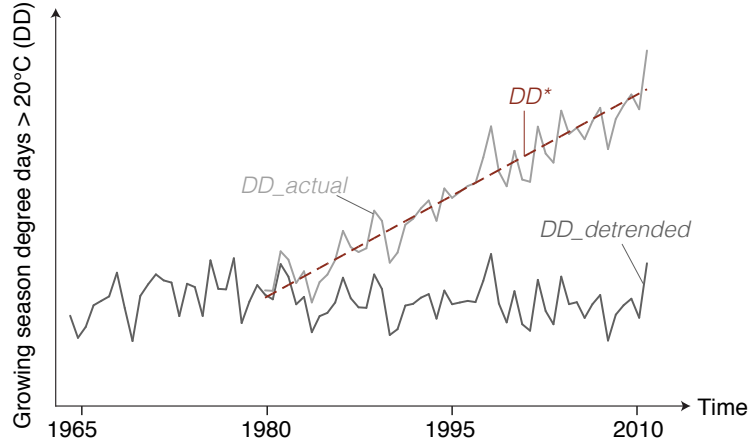


Figure S3: Identifying counterfactual de-trended temperatures, adapted from [7]

state and each year to recover the additional number of suicide deaths. Figure 4 *B* in the main text displays these additional deaths in each year; integrating over states and years gives the cumulative effect of temperature trends for all of India over the entire period since 1980.

1.4 Assumptions behind ordinary least squares

Throughout this article, I estimate the effect of climate on suicide using ordinary least squares (OLS). It is also possible to model suicide events using nonlinear count models, such as Poisson regression or negative binomial regression, and these approaches may be preferable to OLS when the conditional distribution of the dependent variable is poorly approximated by a normal distribution. While other analyses have modeled causes of suicide using count models (e.g. [14]), I use OLS for two reasons: the relative weakness of assumptions required for consistent estimation of causal effects, and its ease of interpretation.

Distributional assumptions on either the disturbances or the outcome variable, such as normality, are not required in order for OLS regression coefficients to consistently estimate a true population parameter [23]. However, normality of the disturbances is an assumption used to estimate critical values for inference in finite samples. As count data are aggregated to coarser levels of spatial and temporal aggregation, it becomes more likely that the conditional distribution of the outcome variable approximates a normal distribution. In my case, my state-by-year observations are relatively coarse measures. Reassuringly, the residuals from my main regression model very closely approximate a normal distribution, as shown in Figure S4.

In contrast, the assumptions imposed by count models can be much more restrictive. For example,

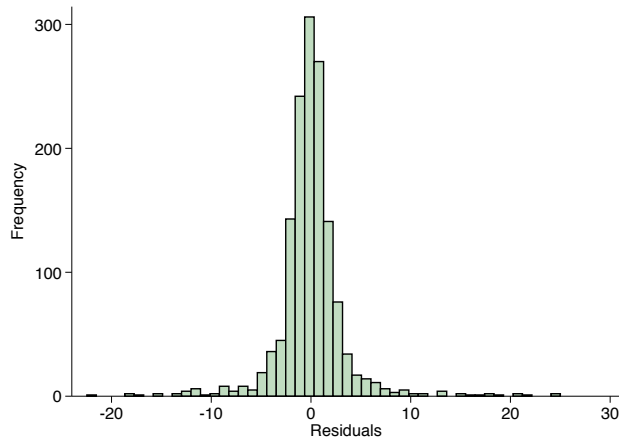


Figure S4: Distribution of residuals from regression model in Equation 2

modeling the data generating process as Poisson imposes the restriction that the mean and variance of the outcome variable are identical (as shown in Table S1, this is not the case in my data). Moreover, the coefficients derived from count models are much more difficult to interpret than those derived from OLS. I therefore follow the literature on climate and mortality (e.g. [10]), as well as the literature studying the socioeconomic drivers of suicide in aggregate panel data (e.g. [1]), and use OLS with the state-by-year suicide rate as an outcome variable.

2 Supplementary tables

2.1 Effect of heat exposure and precipitation on suicide rates and yield values

	<i>Suicides per 100,000</i>			<i>100×Log yield (rupees/ha)</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
Growing seas. degree days below threshold (°C)	0.003*** (0.001)	0.000 (0.001)	0.004*** (0.001)	0.013 (0.009)	-0.019 (0.018)	-0.003 (0.013)
Growing seas. degree days (°C)	0.007*** (0.002)	0.009** (0.004)	0.008** (0.003)	-0.017*** (0.006)	-0.020* (0.010)	-0.019* (0.010)
Nongrowing seas. degree days below threshold (°C)	-0.001 (0.001)	-0.009* (0.004)	-0.003* (0.002)	0.002 (0.003)	0.007 (0.005)	0.001 (0.004)
Nongrowing seas. degree days (°C)	-0.002* (0.001)	0.002 (0.003)	0.001 (0.003)	0.010*** (0.004)	0.018*** (0.006)	0.010* (0.006)
Growing seas. precip. (cm)	0.115 (0.147)	0.251 (0.176)	0.183 (0.152)	6.048*** (0.712)	4.255*** (0.638)	4.422*** (0.653)
Growing seas. precip. ² (cm ²)	-0.026 (0.020)	-0.027 (0.019)	-0.022 (0.017)	-0.870*** (0.133)	-0.653*** (0.117)	-0.681*** (0.122)
Growing seas. precip. ³ (cm ³)	0.001* (0.000)	0.000* (0.000)	0.000 (0.000)	0.030*** (0.005)	0.023*** (0.004)	0.024*** (0.004)
Nongrowing seas. precip. (cm)	-0.031 (0.206)	0.097 (0.221)	0.033 (0.237)	1.496** (0.596)	2.974*** (0.775)	3.103*** (0.746)
Nongrowing seas. precip. ² (cm ²)	0.013 (0.030)	0.003 (0.035)	0.014 (0.033)	0.282 (0.323)	-0.300 (0.401)	-0.365 (0.377)
Nongrowing seas. precip. ³ (cm ³)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.071* (0.037)	-0.018 (0.050)	-0.011 (0.045)
Observations	1,434	1,434	1,434	11,289	11,289	11,289
R-squared	0.908	0.893	0.916	0.840	0.842	0.849
State Trends	YES		YES	YES		YES
Year FE		YES	YES		YES	YES

Table S2: Effect of heat exposure and precipitation on suicide rates and yield values, by agricultural season

Notes: Temperature coefficients represent the effect of one day becoming 1°C warmer on the annual suicide rate (suicide deaths per 100,000 people) or annual yield (log rupees/ha), where temperature effects are differentially estimated for days below 20°C and above 20°C and for the growing and nongrowing seasons in India. Precipitation coefficients represent the effect of seasonal cumulative rainfall increasing by 1cm on the annual suicide rate and annual yield. Columns (1)–(3) include state fixed effects and report standard errors clustered at the state level. Columns (4)–(6) include district fixed effects and report standard errors clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

2.2 Robustness to fixed effects specifications

	<i>Suicides per 100,000</i>			
	(1) OLS	(2) State FE	(3) State FE + State Trends	(4) State & Yr FE + State Trends
Growing seas. degree days below threshold (°C)	0.0046 (0.0053)	-0.0040*** (0.0010)	0.0026*** (0.0008)	0.0037*** (0.0008)
Growing seas. degree days (°C)	-0.0020 (0.0040)	0.0175*** (0.0035)	0.0066*** (0.0023)	0.0079** (0.0031)
Nongrowing seas. degree days below threshold (°C)	-0.0038 (0.0025)	-0.0036 (0.0040)	-0.0009 (0.0010)	-0.0027* (0.0016)
Nongrowing seas. degree days (°C)	0.0159*** (0.0040)	0.0029 (0.0026)	-0.0020* (0.0011)	0.0014 (0.0026)
Growing seas. precip. (cm)	0.1083 (0.8147)	0.3407* (0.1703)	0.1150 (0.1465)	0.1826 (0.1522)
Growing seas. precip. ² (cm ²)	-0.0071 (0.0789)	-0.0510** (0.0216)	-0.0264 (0.0196)	-0.0218 (0.0171)
Growing seas. precip. ³ (cm ³)	-0.0001 (0.0013)	0.0009*** (0.0003)	0.0006* (0.0003)	0.0004 (0.0002)
Nongrowing seas. precip. (cm)	1.1920* (0.6845)	0.0673 (0.2126)	-0.0312 (0.2060)	0.0327 (0.2367)
Nongrowing seas. precip. ² (cm ²)	0.0406 (0.1395)	-0.0000 (0.0326)	0.0133 (0.0300)	0.0142 (0.0330)
Nongrowing seas. precip. ³ (cm ³)	-0.0065 (0.0066)	-0.0005 (0.0013)	-0.0009 (0.0011)	-0.0009 (0.0011)
Observations	1,434	1,434	1,434	1,434
R-squared	0.478	0.871	0.908	0.916
State FE		YES	YES	YES
State Trends			YES	YES
Year FE				YES

Table S3: Robustness of the suicide degree day model to various fixed effects specifications

Notes: Regression includes annual data for 32 Indian states between 1967 and 2013. Growing season is June-September, nongrowing season contains all other months. Degree day cutoff is 20°C. Standard errors are clustered at the state level.
*** p<0.01, ** p<0.05, * p<0.1.

	<i>Log yield (rupees per ha)</i>			
	(1)	(2)	(3)	(4)
	OLS	District FE	District FE + State Trends	District & Yr FE + State Trends
Growing seas. degree days below threshold (°C)	0.2557*** (0.0377)	-0.0116 (0.0348)	0.0133 (0.0090)	-0.0027 (0.0127)
Growing seas. degree days (°C)	-0.0376** (0.0149)	0.1453*** (0.0114)	-0.0173*** (0.0060)	-0.0191* (0.0097)
Nongrowing seas. degree days below threshold (°C)	-0.0425*** (0.0107)	-0.0784*** (0.0056)	0.0019 (0.0034)	0.0012 (0.0044)
Nongrowing seas. degree days (°C)	0.0007 (0.0124)	0.0020 (0.0075)	0.0101*** (0.0038)	0.0100* (0.0056)
Growing seas. precip. (cm)	0.6421 (2.6620)	8.8834*** (0.8961)	6.0476*** (0.7121)	4.4222*** (0.6529)
Growing seas. precip. ² (cm ²)	-0.1911 (0.4707)	-1.4395*** (0.1730)	-0.8697*** (0.1332)	-0.6812*** (0.1222)
Growing season precip. ³ (cm ³)	0.0155 (0.0181)	0.0483*** (0.0065)	0.0296*** (0.0048)	0.0238*** (0.0044)
Nongrowing seas. precip. (cm)	26.9092*** (2.3122)	14.8560*** (1.3260)	1.4962** (0.5958)	3.1032*** (0.7457)
Nongrowing seas. precip. ² (cm ²)	-7.6716*** (1.3907)	-6.4903*** (1.0047)	0.2816 (0.3230)	-0.3646 (0.3765)
Nongrowing season precip. ³ (cm ³)	0.6476*** (0.1599)	0.5919*** (0.1419)	-0.0710* (0.0372)	-0.0114 (0.0450)
Observations	11,289	11,289	11,289	11,289
R-squared	0.225	0.666	0.839	0.848
District FE		YES	YES	YES
Year FE				YES
State Trends			YES	YES

Table S4: Robustness of the yield degree day model to various fixed effects specifications

Notes: Regression includes annual district-level data for 13 Indian states between 1956 and 2000. Growing season is June-September, Nongrowing season contains all other months. Degree day cutoff is 20°C. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

2.3 Robustness to weighting schemes for climate data aggregation

	<i>Suicides per 100,000</i>			<i>100×Log yield (rupees/ha)</i>		
	(1) area weighted	(2) crop weighted	(3) pop weighted	(4) area weighted	(5) crop weighted	(6) pop weighted
Growing seas. degree days below threshold (°C)	0.0026*** (0.0008)	0.0032*** (0.0004)	0.0032*** (0.0005)	0.0133 (0.0090)	0.0180* (0.0097)	0.0177* (0.0099)
Growing seas. degree days (°C)	0.0066*** (0.0023)	0.0050*** (0.0016)	0.0058*** (0.0019)	-0.0173*** (0.0060)	-0.0171*** (0.0060)	-0.0170*** (0.0060)
Nongrowing seas. degree days below threshold (°C)	-0.0009 (0.0010)	-0.0010 (0.0009)	-0.0009 (0.0009)	0.0019 (0.0034)	0.0014 (0.0040)	0.0011 (0.0040)
Nongrowing seas. degree days (°C)	-0.0020* (0.0011)	-0.0021** (0.0001)	-0.0021** (0.0001)	0.0101*** (0.0038)	0.0103*** (0.0038)	0.0104*** (0.0038)
Growing Seas. precip (cm)	0.1150 (0.1465)	0.0159 (0.0625)	0.1689 (0.1722)	6.0476*** (0.7121)	6.0430*** (0.7154)	6.0390*** (0.7153)
Growing seas. precip. ² (cm ²)	-0.0264 (0.0196)	-0.0127 (0.0076)	-0.0340 (0.0240)	-0.8697*** (0.1332)	-0.8687*** (0.1336)	-0.8680*** (0.1336)
Growing seas. precip. ³ (cm ³)	0.0006* (0.0003)	0.0005** (0.0002)	0.0007* (0.0004)	0.0296*** (0.0048)	0.0296*** (0.0049)	0.0295*** (0.0049)
Nongrowing seas. precip (cm)	-0.0312 (0.2060)	-0.2630** (0.1222)	-0.0460 (0.2160)	1.4962** (0.5958)	1.4964** (0.5982)	1.4982** (0.5980)
Nongrowing seas. precip. ² (cm ²)	0.0133 (0.0300)	0.0498 (0.0300)	0.0195 (0.0319)	0.2816 (0.3230)	0.2829 (0.3238)	0.2818 (0.3238)
Nongrowing seas. precip. ³ (cm ³)	-0.0009 (0.0011)	-0.0025* (0.0014)	-0.0013 (0.0014)	-0.0710* (0.0372)	-0.0712* (0.0372)	-0.0710* (0.0372)
Observations	1,434	1,387	1,434	11,289	11,289	11,289
R-squared	0.9083	0.9141	0.9086	0.8401	0.8401	0.8401

Table S5: Robustness of the degree day model to different weighting schemes for aggregation of climate data

Notes: Regressions in columns (1)–(3) include annual data for 32 Indian states between 1967 and 2013, and in columns (4)–(6) include annual data for all districts in 13 Indian states between 1956 and 2000. Growing season is June–September, nongrowing season contains all other months. Degree day cutoff is 20°C. Columns (1)–(3) include state fixed effects and report standard errors clustered at the state level. Columns (4)–(6) include district fixed effects and report standard errors clustered at the district level. All regressions include state-specific linear trends. Crop weights for each grid cell are cropped area fraction; population weights for each grid cell are total population in 2010. *** p<0.01, ** p<0.05, * p<0.1.

2.4 Robustness to degree day cutoff values

	<i>Suicides per 100,000</i>		
	(1) 15°C	(2) 20°C	(3) 25°C
Growing seas. degree days below threshold (°C)	0.0026*** (0.0009)	0.0026*** (0.0008)	0.0024** (0.0009)
Growing seas. degree days (°C)	0.0062*** (0.0021)	0.0066*** (0.0023)	0.0087** (0.0033)
Nongrowing seas. degree days below threshold (°C)	-0.0009 (0.0013)	-0.0009 (0.0010)	-0.0009 (0.0010)
Nongrowing seas. degree days (°C)	-0.0017 (0.0010)	-0.0020* (0.0011)	-0.0027 (0.0022)
Growing seas. precip (cm)	0.1079 (0.1450)	0.1150 (0.1465)	0.1376 (0.1511)
Growing seas. precip. ² (cm ²)	-0.0258 (0.0195)	-0.0264 (0.0196)	-0.0283 (0.0200)
Growing seas. precip. ³ (cm ³)	0.0006* (0.0003)	0.0006* (0.0003)	0.0006* (0.0003)
Nongrowing seas. precip (cm)	-0.0293 (0.2059)	-0.0312 (0.2060)	-0.0303 (0.2085)
Nongrowing seas. precip. ² (cm ²)	0.0132 (0.0301)	0.0133 (0.0300)	0.0135 (0.0305)
Nongrowing seas. precip. ³ (cm ²)	-0.0009 (0.0011)	-0.0009 (0.0011)	-0.0009 (0.0011)
Observations	1,434	1,434	1,434
R-squared	0.9083	0.9083	0.9084

Table S6: Robustness of the suicide degree day model to different degree day cutoffs

Notes: Regressions include annual data for 32 Indian states between 1967 and 2013. Growing season is June-September, nongrowing season contains all other months. All regressions include state-specific linear time trends. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

	<i>100 × Log yield (rupees per ha)</i>		
	(1)	(2)	(3)
	15°C	20°C	25°C
Growing seas. degree days below threshold (°C)	0.0113 (0.0093)	0.0133 (0.0090)	0.0272*** (0.0082)
Growing seas. degree days (°C)	-0.0164*** (0.0058)	-0.0173*** (0.0060)	-0.0270*** (0.0078)
Nongrowing seas. degree days below threshold (°C)	0.0090* (0.0054)	0.0019 (0.0034)	-0.0029 (0.0027)
Nongrowing seas. degree days (°C)	0.0052* (0.0029)	0.0101*** (0.0038)	0.0251*** (0.0058)
Growing seas. precip (cm)	6.1603*** (0.7099)	6.0476*** (0.7121)	5.6173*** (0.6877)
Growing seas. precip. ² (cm ²)	-0.8844*** (0.1327)	-0.8697*** (0.1332)	-0.8136*** (0.1297)
Growing Season precip. ³ (cm ³)	0.0300*** (0.0048)	0.0296*** (0.0048)	0.0279*** (0.0047)
Nongrowing seas. precip (cm)	1.4283** (0.5975)	1.4962** (0.5958)	1.6163*** (0.5969)
Nongrowing seas. precip. ² (cm ²)	0.3065 (0.3244)	0.2816 (0.3230)	0.1888 (0.3204)
Nongrowing seas. precip. ³ (cm ³)	-0.0736** (0.0371)	-0.0710* (0.0372)	-0.0598 (0.0371)
Observations	11,289	11,289	11,289
R-squared	0.8387	0.8388	0.8395

Table S7: Robustness of the yield degree day model to different degree day cutoffs

Notes: Regressions include annual data for all districts in 13 Indian states between 1956 and 2000. Growing season is June-September, nongrowing season contains all other months. All regressions include state-specific linear time trends. Standard errors are clustered at the district level. *** p<0.01, ** p<0.05, * p<0.1.

2.5 Robustness to alternative temporal adjustments

	(1)	(2)	(3)	(4)
	Linear trends	Quad. trends	Linear trends + Year FE	Quad. trends + Year FE
Growing seas. degree days below threshold (°C)	0.0026*** (0.0008)	0.0035*** (0.0011)	0.0037*** (0.0008)	0.0046*** (0.0008)
Growing seas. degree days (°C)	0.0066*** (0.0023)	0.0064** (0.0024)	0.0079** (0.0031)	0.0082** (0.0031)
Nongrowing seas. degree days below threshold (°C)	-0.0009 (0.0010)	-0.0009 (0.0010)	-0.0027* (0.0016)	-0.0018 (0.0013)
Nongrowing seas. degree days (°C)	-0.0020* (0.0011)	-0.0015 (0.0011)	0.0014 (0.0026)	0.0024 (0.0025)
Growing seas. precip. (cm)	0.1150 (0.1465)	0.1030 (0.1447)	0.1826 (0.1522)	0.2166 (0.1502)
Growing seas. precip. ² (cm ²)	-0.0264 (0.0196)	-0.0268 (0.0192)	-0.0218 (0.0171)	-0.0253 (0.0172)
Growing seas. precip. ³ (cm ³)	0.0006* (0.0003)	0.0006* (0.0003)	0.0004 (0.0002)	0.0005* (0.0002)
Nongrowing seas. precip. (cm)	-0.0312 (0.2060)	0.0125 (0.1994)	0.0327 (0.2367)	0.0421 (0.2426)
Nongrowing seas. precip. ² (cm ²)	0.0133 (0.0300)	0.0049 (0.0299)	0.0142 (0.0330)	0.0152 (0.0343)
Nongrowing seas. precip. ³ (cm ²)	-0.0009 (0.0011)	-0.0006 (0.0011)	-0.0009 (0.0011)	-0.0009 (0.0012)
Observations	1,434	1,434	1,434	1,434
R-squared	0.9083	0.9091	0.9163	0.9173
Linear State Trends	YES		YES	
Quad. State Trends		YES		YES
Year FE			YES	YES

Table S8: Robustness of the suicide degree day model to different time-varying controls

Notes: Regressions include annual data for 32 Indian states between 1967 and 2013. Growing season is June-September, nongrowing season contains all other months. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

2.6 Panel of long differences

	(1) Deg. days 20°C	(2) Deg. days 20°C	(3) Deg. days 25°C	(4) Deg. days 25°C
Growing seas. degree days (°C)	0.023 (0.021)	0.020 (0.020)	0.037 (0.031)	0.023 (0.026)
Nongrowing Seas. degree days (°C)	-0.012 (0.012)	-0.004 (0.011)	-0.013 (0.016)	0.008 (0.017)
Growing seas. precip (cm)	-0.844** (0.340)	-0.731 (0.438)	-0.829** (0.313)	-0.723* (0.418)
Nongrowing seas. precip (cm)	-0.378 (0.452)	-0.020 (0.472)	-0.360 (0.417)	-0.027 (0.456)
Observations	116	116	116	116
R-squared	0.408	0.479	0.408	0.478
State FE	YES	YES	YES	YES
Time Period FE		YES		YES

Table S9: Panel of long differences

Notes: Dependent variable in all regressions is the decadal difference in the smoothed suicide rate, where the data are organized as a 4-period panel of 10-year differences. Periods are 1970-1980, 1980-1990, 1990-2000 and 2000-2010. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

2.7 Irrigation as adaptation

I test whether irrigation is effective at mitigating the temperature response of suicide. I use Ministry of Agriculture data to classify states as heavily irrigated if their share of crop area under irrigation ever exceeds 50% during my sample period. Table S10 shows precipitation and temperature effects on suicide for irrigated and rain-fed states separately. While the results indicate that on average irrigated states have lower suicide rates, accounting for irrigation does not change the findings of my main model, nor is it an identifiable means of adaptation to high temperatures.

	(1)	(2)	(3)
	Baseline Model	Irrigation & Temp	Irrigation & Precip
Growing seas. degree days ($^{\circ}\text{C}$)	0.0056*** (0.0020)	0.0056** (0.0028)	0.0049** (0.0021)
Nongrowing seas. degree days ($^{\circ}\text{C}$)	-0.0016 (0.0011)	-0.0021* (0.0012)	-0.0021* (0.0012)
Growing seas. precip (cm)	-0.0789 (0.0475)	-0.0754 (0.0508)	-0.0741 (0.0555)
Nongrowing seas. precip (cm)	-0.0082 (0.0819)	-0.0341 (0.0998)	-0.0343 (0.1003)
Irrigated		-21.8881*** (3.6741)	-23.5120*** (2.3590)
Irrigated \times growing season degree days ($^{\circ}\text{C}$)		-0.0026 (0.0034)	
Irrigated \times growing season precip. (cm)			-0.0105 (0.0729)
Observations	1,434	1,332	1,332
R-squared	0.908	0.907	0.907

Table S10: Heterogeneity in the degree days model by irrigation prevalence

Notes: Regressions include annual data for 32 Indian states between 1967 and 2013. Growing season is June-September, nongrowing season contains all other months. Degree day cutoff is 20°C . All regressions include state-specific linear time trends. Standard errors are clustered at the state level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2.8 Alternative growing season definition

I define the growing season in India to be the months of June through September, based on the average arrival and withdrawal dates of the southwest monsoon, which largely determines the timing of agricultural production throughout the country. However, the monsoon arrives and withdraws differentially throughout India, first arriving in the southeast in late May, and reaching the northwest of the country by the middle of July. Withdrawal occurs in reverse, with the rains first ending in the northeast in early September, but continuing in the southeast until December. Because my approximation of this timing is coarse, in this table I demonstrate robustness of my main results to an alternative definition of the growing season, in which each state is described by a state-specific growing season, the dates of which are obtained from the Indian Meteorological Department.

	<i>Suicides per 100,000</i>		<i>100×Log yield (rupees/ha)</i>	
	(1)	(2)	(3)	(4)
	June-Sep. season	State-specific season	June-Sep. season	State-specific season
Growing seas. degree days (°C)	0.0066*** (0.0023)	0.0072** (0.0032)	-0.0173*** (0.0060)	-0.0177*** (0.0060)
Nongrowing seas. degree days (°C)	-0.0020* (0.0011)	-0.0023* (0.0012)	0.0101*** (0.0038)	0.0100*** (0.0037)
Growing seas. precip. (cm)	0.1150 (0.1465)	0.2327 (0.2391)	6.0476*** (0.7121)	6.1183*** (0.6711)
Growing seas. precip. ² (cm ²)	-0.0264 (0.0196)	-0.0355 (0.0261)	-0.8697*** (0.1332)	-0.8810*** (0.1265)
Growing seas. precip. ³ (cm ³)	0.0006* (0.0003)	0.0007 (0.0004)	0.0296*** (0.0048)	0.0300*** (0.0046)
Nongrowing seas. precip. (cm)	-0.0312 (0.2060)	-0.1927 (0.1697)	1.4962** (0.5958)	1.6372** (0.7688)
Nongrowing seas. precip. ² (cm ²)	0.0133 (0.0300)	0.0296 (0.0333)	0.2816 (0.3230)	-0.0189 (0.5408)
Nongrowing seas. precip. ³ (cm ³)	-0.0009 (0.0011)	-0.0010 (0.0011)	-0.0710* (0.0372)	-0.0389 (0.0821)
Observations	1,434	1,434	11,289	11,289
R-squared	0.908	0.908	0.840	0.840

Table S11: Robustness of the degree day model to state-specific growing season definitions

Notes: Regressions in columns (1)–(2) include annual data for 32 Indian states between 1967 and 2013, and in columns (3)–(4) include annual data for all districts in 13 Indian states between 1956 and 2000. The growing season is defined as June–September in columns (1) and (3), and is defined individually by state using data from the India Meteorological Department on average monsoon arrival and withdrawal dates in columns (2) and (4). The nongrowing season contains all other months. The degree day cutoff is 20°C, and all regressions include state-specific linear time trends. Standard errors are clustered at the state level in columns (1)–(2) and at the district level in columns (3)–(4). *** p<0.01, ** p<0.05, * p<0.1.

2.9 Drought

	<i>Suicides per 100,000</i>		
	(1)	(2)	(3)
Growing seas. degree days (°C)	0.0162*** (0.0036)	0.0059*** (0.0021)	0.0073** (0.0031)
Nongrowing seas. degree days (°C)	0.0033 (0.0025)	-0.0014 (0.0011)	0.0013 (0.0024)
Drought: 20th percentile	-0.3160 (0.3940)	0.0417 (0.3430)	-0.0439 (0.4440)
Surplus: 80th percentile	-0.3770 (0.2750)	-0.3740 (0.2330)	0.2940 (0.3370)
Observations	1,472	1,472	1,472
R-squared	0.869	0.908	0.916
State Trends		YES	YES
Year FE			YES

Table S12: Effect of heat exposure and precipitation on suicide rates and yield values

Notes: Regressions include annual data for 32 Indian states between 1967 and 2013. Temperature coefficients represent the effect of one day becoming 1°C warmer on the annual suicide rate, for days above 20°C in the growing and nongrowing seasons in India. Drought is defined as an indicator equal to one when annual rainfall is in the 20th percentile or below, while surplus is equal to one when annual rainfall is above the 80th percentile, where percentiles are state-specific. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

2.10 Robustness to inclusion of a lagged dependent variable

	<i>Suicides per 100,000</i>	
	(1)	(2)
	Main model	AR model
Lagged suicide rate (suicides/100,000)		0.3195*** (0.0740)
Growing seas. degree days below threshold (°C)	0.0037*** (0.0008)	0.0036*** (0.0009)
Growing seas. degree days (°C)	0.0079** (0.0031)	0.0067* (0.0033)
Growing seas. precip. (cm)	0.1826 (0.1522)	0.1031 (0.1849)
Growing seas. precip. ² (cm ²)	-0.0218 (0.0171)	-0.0151 (0.0215)
Growing seas. precip. ³ (cm ³)	0.0004 (0.0002)	0.0004 (0.0003)
Observations	1,434	1,400
R-squared	0.9163	0.9270

Table S13: Robustness of the suicide degree day model to inclusion of a lagged dependent variable

Notes: Regressions include annual data for 32 Indian states between 1967 and 2013. Growing season is June-September, nongrowing season contains all other months. All regressions include linear state-specific trends and year fixed effects. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

3 Supplementary figures

3.1 Degree days across seasons

One concern with using the pattern matching approach I show in Figure 1 of the main text is that temperature may impact suicide during the growing season months only, but for reasons unrelated to agriculture. In particular, there is some evidence that suicide is directly impacted by heat through a psychological mechanism [8]. However, this direct impact is not identifiable in the nongrowing season, despite the presence of many hot days during this period (Figure S5). Across a variety of robustness checks (Table S3-S10), coefficients on high temperatures in the off-season are consistently close to zero and statistically insignificant, suggesting no strong psychological mechanism is at play.

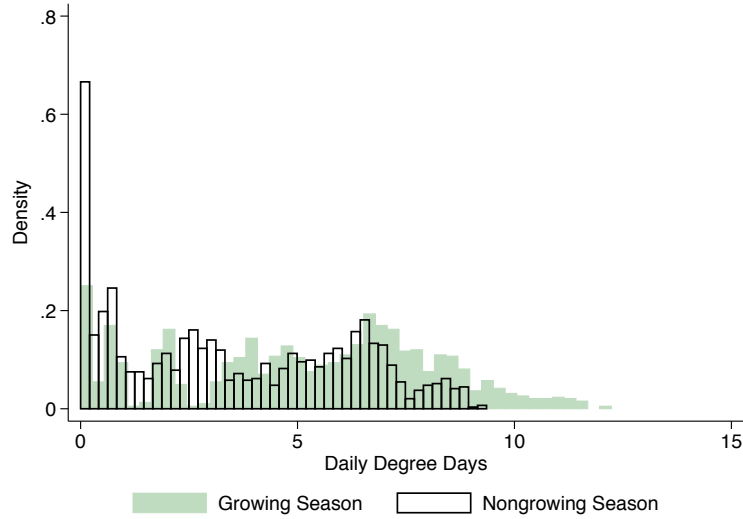


Figure S5: Distribution of cumulative degree days above 20°C in the growing and nongrowing seasons

Notes: This figure shows the distribution of daily degree days above 20°C for the growing and nongrowing seasons, using daily mean temperature for 32 of India’s states between 1967-2013. The growing season is June through September, while the nongrowing season is all other months.

3.2 Robustness of piecewise linear response

Figure S6 shows the robustness of my piecewise linear estimation strategy for temperature to a higher order of flexibility. The dotted lines show the response function when estimating Equation 2 and setting $\kappa = 7$, while the solid lines, as in the main text, show the response function when setting $\kappa = 4$. Temperatures below 10°C are not shown, although are included in the regression.

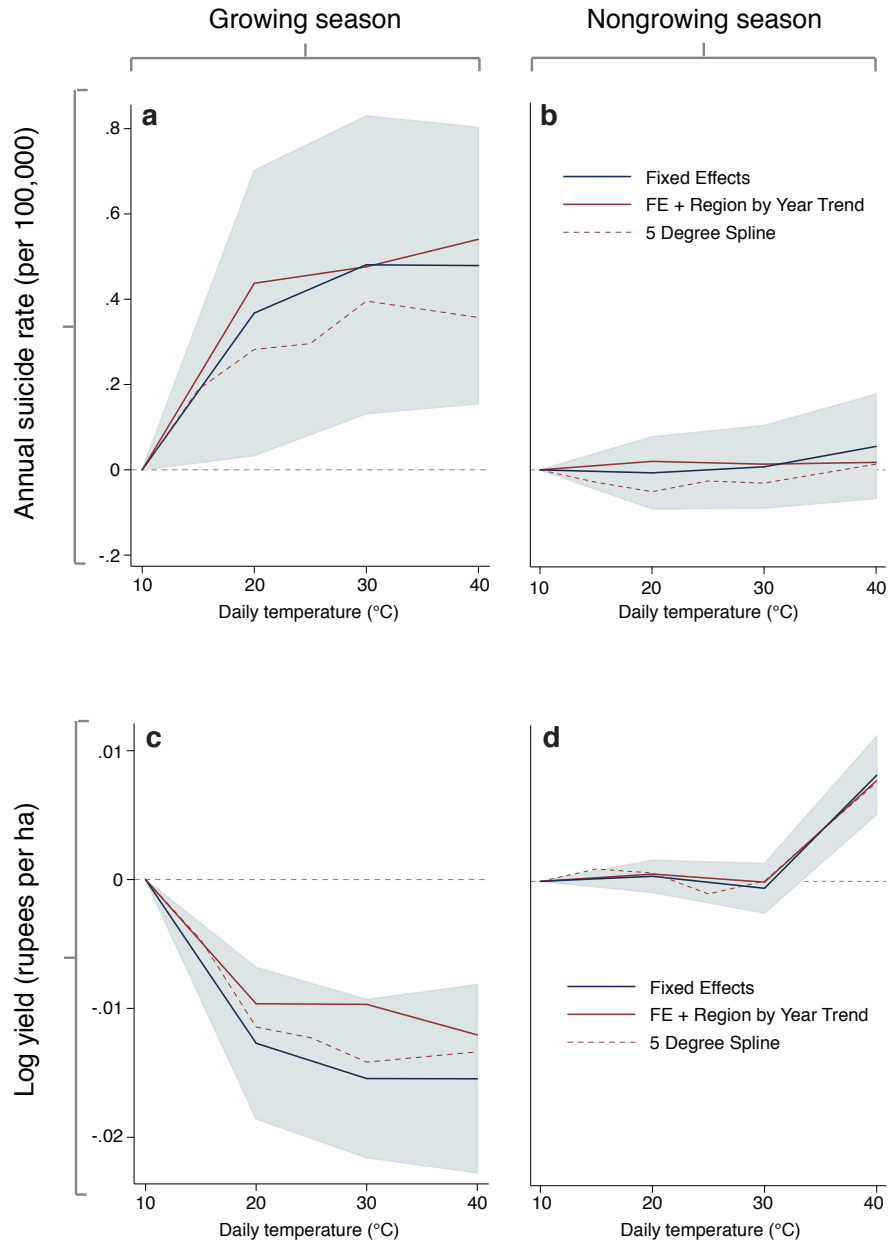


Figure S6: Nonlinear relationship between temperature and suicide rates, and between temperature and yield. **a** and **b** show the response of annual suicides per 100,000 people to growing season (June through September) and nongrowing season (all other months) temperatures, respectively. Panels **c** and **d** show the response of annual log yield, valued in rupees per hectare, to growing season (June through September) and nongrowing season (all other months) temperatures, respectively. The fixed effects regression includes year fixed effects, while the FE + Region by Year Trend regression includes year fixed effects and linear regional time trends. The 5 Degree Spline model estimates a linear spline with knots at every 5°C interval. All graphs are centered at zero.

3.3 Monthly estimation of temperature and precipitation effects

With my main specification, I am unable to reject that rainfall has no effect on suicide rates. This result may be due to my need to characterize monsoon rainfall at the state level, as there can be important within-state differences in monsoon arrival and withdrawal [4]. The higher-resolution district-level agricultural data, in contrast, suffer far less from this problem. Figure S7 suggests measurement error may be at play: this plot of *monthly* rainfall effects illustrates a consistently negative, yet often insignificant, impact of rainfall on suicide rates during the main growing season months.

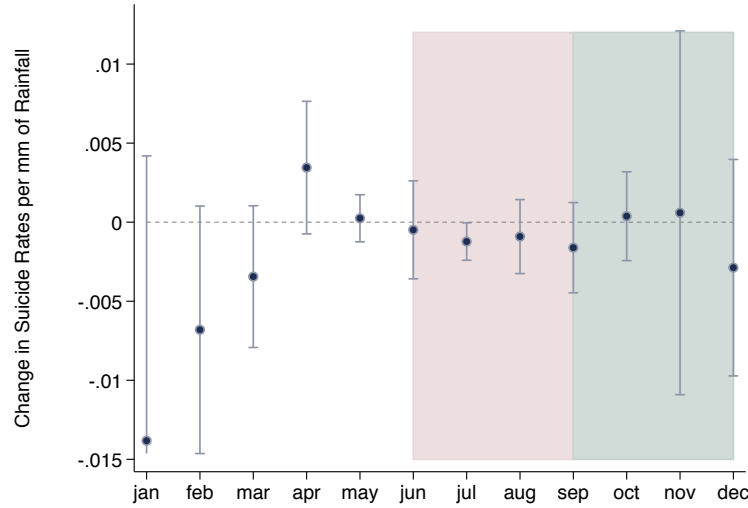


Figure S7: Points represent the marginal effect of one mm of rainfall in each month on suicide deaths per 100,000 people. Shaded pink areas represent the growing season months and shaded green areas represent the harvesting season months, although some states continue to grow crops through October and November.

3.4 Lagged effects

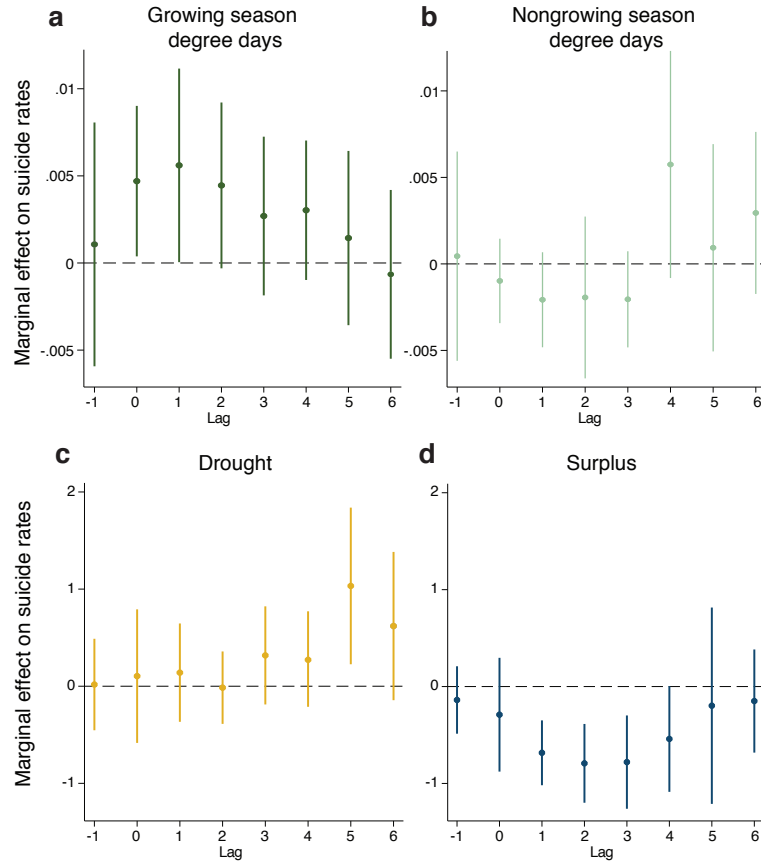


Figure S8: Points represent the marginal effect of degree days (panels **a** and **b**), an indicator for drought (panel **c**), or an indicator for surplus rainfall (panel **d**) on the annual number of suicides per 100,000 people. The x-axis corresponds to the number of annual lags. All coefficients shown in panels **a** and **b** were estimated jointly in a degree days model with a cutoff of 20°C and a cubic polynomial in precipitation; all coefficients shown in panels **c** and **d** were estimated jointly in a degree days model with a cutoff of 20°C where indicators for drought (annual rainfall below state-specific 20th percentile) and surplus (annual rainfall above state-specific 80th percentile) were used instead of continuous rainfall. Standard errors are clustered at the state level, and 95% confidence intervals are shown around each coefficient.

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